The Economics and Econometrics of Damage Control

Atanu Saha, C. Richard Shumway, and Arthur Havenner

Concern for the potentially harmful side effects of agricultural chemical inputs, especially pesticides, highlights the need to accurately determine the economic levels of their use. We consider three model specification issues: interaction of direct production inputs with damage control inputs in damage abatement, justification for a priori exclusion of production inputs from the abatement function, and the motivations and consequences of alternative stochastic specifications. Empirical analysis using farm-level data shows that misspecification of the stochastic element in the production function can overestimate the marginal physical productivity of pesticides and grossly underestimate the responsiveness of demand to increases in pesticide prices.

Key words: damage control, pesticide usage, stochastic production, yield variability

The scientific achievements affecting worldwide agricultural production during the twentieth century are well documented. Malthusian prophecies of famine and starvation from a burgeoning population have not come to pass. Productivity increases have far outstripped population growth and appear likely to continue into the foreseeable future. Much of the crop productivity growth has been due to scientific development and usage of chemical inputs, primarily commercial fertilizers and pesticides, in combination with new high-yielding crop varieties.

The substantial contributions of chemical inputs in enabling farmers to capture full output benefits from new crop varieties are seldom challenged. What receive far greater debate are the secondary effects of chemical use. A positive impact is the need to use less land for food production, especially land most susceptible to erosion, and to retain more land in native condition suitable both as habitat for wildlife and natural amenities for humans (Avery, p. 74). Negative effects are unintended health and environmental hazards. While the greatest individual human risks are for individuals who receive direct occupational exposure (National Research Council), the current public policy debate on agricultural chemical health risks is focused on the broader public, i.e., food and water consumers (Taylor et al.). In the Environmental Protection Agency's (EPA) 1990 national survey of drinking water wells, nitrate (a common fertilizer ingredient) was found in over half of the wells, and at least one pesticide was detected in 10% of the community wells and 4% of the rural wells (USEPA). While it is not clear that residues in small concentrations are harmful, it is clear that groundwater contamination by persistent chemicals is generally irreversible unless an aquifer undergoes substantial drawdown and recharge.

Concern for the potentially harmful side effects of agricultural chemical inputs highlights the need to determine more accurately economic levels of use and to document incentives that could induce farmers to limit their use. Unfortunately, there is little agreement concerning optimal levels of chemical use or concerning the magnitude of incentives needed to limit usage. Many of the differences are traceable to differences in the model specification, and particularly to the specification involving damage control inputs such as pesticides which contribute only indirectly to production. The purpose of this paper is to examine the consequences and implications of alternative model specifications.

Atanu Saha is senior economist at Micronomics, Los Angeles, California, C. Richard Shumway is professor in the Department of Agricultural Economics at Texas A&M University, and Arthur Havenner is professor in the Department of Agricultural Economics at the University of California, Davis. Senior authorship is equally shared.

The authors wish to express appreciation to Larry Langemeier for providing access to extensive unpublished data. All correspondence concerning this paper should be sent to Atanu Saha, Micronomics Inc., 400 S. Hope Street, Twenty-fifth Floor, Los Angeles, CA 90071.

Amer. J. Agr. Econ. 79 (August 1997): 773–785

In the next section, we consider three distinct, yet related, model specification issues: interaction of direct production inputs with damage control inputs in damage abatement; justification for a priori exclusion of production inputs from the abatement function; and motivations for, and consequences of, alternative stochastic specifications. Using farm-level data, formal tests of different specifications are conducted in the following section. We then derive implications relevant to the policy debate on agricultural chemical usage. The final section provides a general overview of the results.

Specification Issues

Few production function forms prevalent in the applied literature admit specification distinctions between production inputs and damage control agents such as pesticides, fire sprinklers, or immunizations. Forms such as the Cobb-Douglas or translog require all inputs to be strictly positive. In these forms output is undefined if one or more inputs have zero values. In the case of damage control inputs, however, zero usage and positive output are certainly plausible.

Among the widely used production functions, the quadratic and generalized Leontief are ones that can accommodate zero input levels. However, due to additive errors, both specifications imply that inputs have no effect on output variance. This is a severe restriction, especially in the case of inputs that are used to reduce potential losses caused by damage. Usage of such inputs is unlikely to leave the variability of output unchanged.

Analysis of a decision maker's motive for self-insurance through expenditure in loss-reducing agents dates back to Ehrlich and Becker's seminal study. Since then, a number of papers have considered models of loss-reduction in the context of a firm (Pope and Kramer, Hiebert, Dionne and Eeckhoudt). The empirical and analytical literature on damage reduction in the context of agriculture is voluminous. A representative, though not exhaustive, list of studies in this area includes Feder; Regev, Shalit, and Gutierrez; Lichtenberg and Zilberman; and Chambers and Lichtenberg. In almost all the foregoing studies, the firm's production function includes a damage abatement function, with abatement being a function of damage control agents. In contrast to the standard production function, $Q = f(\mathbf{Z}, \mathbf{x})$, these studies propose the following:

$$(1) \quad Q = F[\mathbf{Z}, g(\mathbf{x})]$$

where Q denotes output, $\mathbf{Z}$ is a vector of direct production inputs, $\mathbf{x}$ is a vector of damage-control agents, and $g(\cdot)$ denotes the abatement function. The functional specification of $g(\cdot)$ is assumed to admit the possibility of a positive output level with zero $\mathbf{x}$ usage; i.e., $Q = F[\mathbf{Z}, g(0)] > 0$ is feasible.

Interactive versus Noninteractive Abatement Specification

A key feature of the specification in equation (1) is that it models abatement as depending on damage control inputs, independent of all other inputs. Consequently, equation (1) precludes possible interaction between damage control agents and direct production inputs within the abatement function. In many cases, this interaction can have considerable influence on the productivity of damage control agents. For example, the effectiveness of certain pesticides may be significantly changed not only by their level of use but also by moisture levels in soil during and after their application. In other words, the damage control agent "pesticide" and the direct production input "irrigation water" may have a significant interactive effect on pest control. Another example is the interaction between fertilizer and herbicides in which fertilizer stimulates the growth of weeds, thus changing the effectiveness of herbicides. In many cases, labor and farm machinery play dual roles of production input and damage control agent, and the interaction between them is particularly evident during harvest when a rapid response may be crucial in reducing potential crop losses from adverse conditions (e.g., imminent frost for vegetables like tomatoes or late rain for many crops).

The possible interaction of damage control and direct production inputs can be formally incorporated through an "interactive" damage abatement function:

$$(2) \quad Q = G[\mathbf{Z}, g(\mathbf{x}, \mathbf{z})]$$

where $\mathbf{z} \subseteq \mathbf{Z}$, i.e., a subset of direct production inputs enters the abatement function. This specification allows a subset of inputs, $\mathbf{z}$, to have dual roles: direct production and damage abatement.

When interactions between direct production inputs and damage control agents are explicitly modeled within the abatement function, both the marginal productivity of damage control agents and their threshold prices may differ markedly. Threshold price is the price at which the decision maker is indifferent between using some damage control agent and none at all (Weersink, Deen, and Weaver). Our empirical analysis shows that the marginal product and threshold level estimates are extremely sensitive to the specification of the abatement function.

Separability

In contrast to the traditional production function, $Q = f(\mathbf{Z}, \mathbf{x})$, the specifications in both equations (1) and (2) imply separability between subsets of inputs (Blackorby, Primont, and Russell). The marginal rate of substitution among each pair of inputs in $\mathbf{x}$ is presumed to be independent of the level of each input that belongs to $\mathbf{Z}$ in the case of equation (1) and to the complement $\mathbf{z}$ in the case of equation (2). If the production function is weakly separable in an exhaustive partition of inputs, such as $\mathbf{Z}$ from $\mathbf{x}$, and $\mathbf{x}$ from $\mathbf{Z}$ (where $\mathbf{x}$ is again a vector) in equation (1), then Q can be written as a function of two aggregator functions; i.e., $Q = f[h(\mathbf{Z}), g(\mathbf{x})]$. Because one must decide which inputs not to include in $g(\cdot)$, the issue of separability becomes even more important under the interactive specification (2) and warrants appropriate pretesting.[1]

Stochastic Structure

Another issue with important empirical implications is the stochastic specification of the production function estimation equation. We consider three error specifications. The first, form I, has been used widely in applied studies on damage control. Forms II and III are unique to this study.

Consider the following parameterization of equation (2) which we will denote as form I:

$$Q = F[\mathbf{s}, \mathbf{z}, \beta] \cdot g(\mathbf{x}, \mathbf{z}, \alpha) \cdot \exp(\varepsilon) \qquad (3) \quad \text{(form I)}$$

where $\mathbf{s}$ is the vector of the direct production inputs that do not enter the damage abatement function denoted by $g(\cdot)$, $\mathbf{z}$ denotes the vector of direct production inputs that interact with the damage control agents within $g(\cdot)$, α and β are parameter vectors, and ε denotes a random variable. The noninteractive variant of this form, that is, with all elements of $\mathbf{z}$ in $g(\cdot)$ being zero, has generally been used in empirical studies cited earlier. In these papers, the logarithmic form of equation (3) has been estimated with the additive error ε. For this form, the abatement function $g(\cdot)$ is exact—if you spray, you kill all the pest—and the only stochastic element enters as a multiplicative error [$\exp(\varepsilon)$ in equation (3)]. As a consequence of the multiplicative error in equation (3), the mean and variance effects of any input will be identical in sign. Since a negative mean effect is implausible, form I specification precludes output variance reducing inputs.

An alternative stochastic structure embodies the idea that both environmental and economic considerations often lead to application of damage control inputs at levels that do not entirely devastate the pest and therefore have random elements in their ultimate effects. For example, a very dilute solution of glyphosate (Roundup®) is often used on tree and vine crops to "chemically mow" weeds both to save money and to leave plant structure in the field for erosion control, etc. Since different varieties of weeds have different susceptibilities to the herbicide, the ultimate effect is a stochastic abatement function depending on the distribution of varieties of weeds:

$$Q = F(\mathbf{s}, \mathbf{z}, \beta) \cdot g(\mathbf{x}, \mathbf{z}, \alpha, e) \qquad (4) \quad \text{(form II)}$$

where e denotes a random variable, and all other variables and parameters have the same interpretation as before. The specification in equation (4) with stochastic element in the abatement function but not in the direct production part $F(\cdot)$ will be called form II.

A natural consequence of form II's error structure is that it allows both variance increasing and variance decreasing inputs. Using a first-order Taylor series expansion at the mean, the first two moments of output under form II are given by

$$E[Q] \cong F(\cdot) \cdot g(\mathbf{x}, \mathbf{z}, \boldsymbol{\alpha}, \bar{e}) \qquad (5a)$$

---

[1] Input separability has not been adequately tested in the damage control literature. Chambers and Lichtenberg demonstrated that separability between damage control inputs and other inputs, as in equation (1), implies conditional additivity of profit functions. They also rejected the hypothesis that a conventional specification of the profit function was preferred to their additive form. However, they did not test whether specification (2) was preferred to (1) or whether alternative subsets of inputs belonged to the complement of $\mathbf{z}$ in $\mathbf{Z}$ for specification (2).

and

(5b) $V[Q] \cong F(\cdot)^2 \cdot g_e^2 \cdot \sigma_e^2$

where $\bar{e}$ and σ_e^2 denote the mean and variance of e, and g_e denotes $\partial g/\partial e$. The mean and variance effects of x_k, the kth damage control input, are given by

(6a) $$\frac{\partial E[Q]}{\partial x_k} = F(\cdot) \cdot g_{x_k}(\cdot)$$

and

(6b) $$\frac{\partial \operatorname{var}[Q]}{\partial x_k} = 2F(\cdot)^2 \cdot g_e(\cdot) \cdot g_{ex_k}(\cdot) \cdot \sigma_e^2.$$

It is clear from the above that the signs of the mean and variance effect of x_k depend on the signs of the terms g_{x_k}, g_ε, and $g_{\varepsilon x_k}$. Thus, a mean-increasing and variance-decreasing input is not precluded in form II. In addition, how a damage-control input affects output mean and variance is determined, in part, by the interaction between the input and the stochastic element in the abatement function.

A specification that is more general than forms I and II and includes both as special cases is

(7) $$Q = F(\mathbf{s}, \mathbf{z}, \beta) \cdot g(\mathbf{x}, \mathbf{z}, \alpha, e) \cdot \exp(\varepsilon).$$ (form III)

This specification, which we call form III, combines features of the preceding two forms' error structures. The interpretation of the two stochastic elements in equation (7) is intuitive in the context of agricultural production. The random variable e captures the stochastic nature of the damage abatement process; for example, the effectiveness of pesticides depends on such factors as timing, application uniformity, pest distribution, humidity, and the moisture content of soil. However, even if damage due to pests, weeds, etc., were absent, farm production would still be affected by the variability of rainfall, temperature, length of the growing season, and other factors beyond the producer's control. It is this randomness in the overall production process that is reflected by the variable ε.

Plausibly, the two stochastic variables ε and e will have nonzero covariance. This covariance considerably complicates the expressions for output mean and variance. Fortunately, assuming the exponential form for the damage abatement function (which is empirically plausible and widely used) and normality for the distributions of the two random variables (motivated by the central limit theorem) yields a tractable specification that allows exact formulation of the mean and variance of output. Formally,

ASSUMPTION A1. *$g(\mathbf{x}, \mathbf{z}, \alpha, e) \equiv \exp[-A(\mathbf{x}, \mathbf{z}, \alpha)e]$ where $A(\cdot)$ is a continuous and differentiable function.*

ASSUMPTION A2. *$\varepsilon \sim N(0, 1)$, $e \sim N(\mu, 1)$ and $\operatorname{cov}(\varepsilon, e) \equiv \rho$ where $\sim N(\cdot)$ denotes normally distributed.*

Under A1, taking the logarithm of both sides of equation (7) yields

(8) $$\ln Q = \ln F(\cdot) + \vartheta$$

where $\vartheta \equiv \varepsilon - A(\cdot)e$ is the heteroskedastic error term. Therefore, under A2,

(9) $$\ln Q \sim N[\ln F(\cdot) - \mu A(\cdot),\ B(\cdot)]$$

where $B(\cdot) \equiv \sigma_v^2 \equiv [1 + A(\cdot)^2 - 2A(\cdot)\rho]$. The loglikelihood function (LLF) for the estimation of the parameter vectors α, β, and the distribution parameters μ and ρ is

(10) $$LLF(\alpha, \beta, \mu, \rho) = \frac{n}{2}\ln 2\pi - \frac{1}{2}\sum_i \left\{ \ln B_i(\cdot) + \frac{[\ln Q_i - \ln F_i(\cdot) + \mu A_i(\cdot)]^2}{B_i(\cdot)} \right\}$$

where the subscript i denotes the ith of n observations. The LLF in equation (10) can be maximized by standard nonlinear techniques to get the ML estimates of α, β, μ, and ρ.

Assumption A2 allows us to derive the expressions for output moments. Using the result on the moments of the lognormal distribution, it is readily verified from equation (9) that for form III

(11a) $$E[Q] \equiv \bar{Q} = F(\cdot) \cdot \exp\left[\frac{B(\cdot)}{2} - \mu A(\cdot)\right]$$

and

(11b) $$V(Q) = \bar{Q}^2 \cdot \{\exp[B(\cdot)] - 1\}$$

where $A(\cdot)$ and $B(\cdot)$ have been defined earlier.[2] It is worth reiterating that equations (11a) and (11b) provide exact output moments, not approximations based on Taylor's series expansion.

The effects of various inputs on the mean and variance of output now can be derived using equations (11a) and (11b). The expressions for these effects are presented below under the assumption that the function $F(\cdot)$ in equation (7) has the Cobb-Douglas form, i.e., $F(\cdot) = \Pi_k S_k^{\beta_{s_k}} z_k^{\beta_{z_k}}$. Although the Cobb-Douglas form is restrictive, it is assumed here for the ease of exposition. Importantly, the expressions for the effects can be easily modified for other, less restrictive, specifications for $F(\cdot)$.

Differentiation of equation (11a) with respect to x_k, the kth damage control input, yields, after some simplification,

$$\text{(12a)} \quad \frac{\partial \bar{Q}}{\partial x_k} = \bar{Q} \cdot \{A(\,) - \rho - \mu\} \cdot A_{x_k}$$

where $A_{x_k} \equiv \partial A(\cdot)/\partial x_k$. Similarly, after considerable simplification (the details are available from the authors on request),

$$\text{(12b)} \quad \frac{\partial V(Q)}{\partial x_k} = 2\bar{Q}^2 \quad A_{x_k} \cdot \left\{\exp[B(\cdot)] \cdot [2A(\cdot) - 2\rho - \mu] - [A(\cdot) - \rho - \mu]\right\}.$$

It is evident from equations (12a) and (12b) that, in this formulation, the mean and variance effect of a damage control input can differ in sign.

For z_k, the kth element of the vector of inputs that is common to the functions $F(\cdot)$ and $g(\cdot)$ in equation (8), the expressions for mean and variance effects are

$$\text{(13a)} \quad \frac{\partial \bar{Q}}{\partial z_k} = \bar{Q} \cdot \left\{\frac{\beta_{z_k}}{z_k} + [A(\cdot) - \rho - \mu] \cdot A_{z_k}\right\}$$

and

$$\text{(13b)} \quad \frac{\partial V(Q)}{\partial z_k} = 2\bar{Q}^2 \cdot \left[\frac{\beta_{z_k}}{z_k} \cdot \{\exp[B(\cdot)] - 1\} + A_{z_k} \cdot \left\{\exp[B(\cdot)] \cdot [2A(\cdot) - 2\rho - \mu] - [A(\cdot) - \rho - \mu]\right\}\right]$$

where β_{z_k} denotes the parameter that corresponds to z_k in the Cobb-Douglas form of $F(\cdot)$. As before, $\partial V/\partial z_k$ can be negative or positive depending on the magnitudes of the various terms in $[\cdot]$ above.

Finally, for s_k, the kth direct production input that enters only $F(\cdot)$ and not $g(\cdot)$, the relevant expressions are

$$\text{(14a)} \quad \frac{\partial \bar{Q}}{\partial s_k} = \frac{\bar{Q}}{s_k} \quad \beta_{s_k}$$

$$\text{(14b)} \quad \frac{\partial V(Q)}{\partial s_k} = 2\bar{Q}^2 \cdot \frac{\beta_{s_k}}{s_k} \cdot \{\exp[B(\cdot)] - 1\}.$$

In contrast to the cases for the input entering the damage abatement function, the mean and variance effects of a pure production input s_k are identical in sign.

So far, we have derived the expressions for output moments and the effects of various inputs on these moments for form III using assumptions A1 and A2. In the remainder of the paper, we continue to maintain these assumptions for forms I and II as well, with appropriate modifications. In particular, for form I, since the random variable e is absent, the output moments are

$$\text{(15)} \quad \bar{Q} = F(\cdot) \exp\left\{\frac{\sigma^2}{2} - A(\cdot)\right\}$$

and

$$V(Q) = \bar{Q}^2 \cdot \{\exp(\sigma^2) - 1\}$$

where assumption A2 is modified to be $\varepsilon \sim N(0, \sigma^2)$. For form II, given $e \sim N(\mu, 1)$, the corresponding expressions are

$$\text{(16)} \quad \bar{Q} = F(\cdot) \cdot \exp\left\{\frac{A(\cdot)^2}{2} - \mu A(\cdot)\right\}$$

and

$$V(Q) = \bar{Q}^2 \cdot \{\exp[A(\cdot)^2] - 1\}.$$

Comparison of equations (15) and (16) to equation (11) reveals that the output moments under forms I and II are special cases of those under form III. The expressions under form I can be derived from equation (11) under the restric-

---

[2] If $y = \ln(x)$ and $y \sim N(\mu, \sigma^2)$ then $E[x] \equiv \bar{x} = \exp[\mu + (\sigma^2/2)]$, $V[x] = \bar{x}^2\{\exp(\sigma^2) - 1\}$. (Mood, Graybill, and Boes, p. 117)

tions $\mu = 1$ and $B(\cdot) = \sigma^2$, while the restriction $B(\cdot) = A(\cdot)^2$ yields the output moments under form II. Importantly, a necessary, though not sufficient, condition for deriving form I or form II from the more general form III is the restriction $\rho = \text{cov}(\varepsilon, e) = 0$; this follows from recalling that in these two forms either ε or e is absent. Therefore, one can easily test the hypothesis that both the competing forms are inappropriate by rejecting the null H_0: $\rho = 0$, using form III's ML estimate.

In the interest of brevity, the expressions for the mean and variance effects of inputs are not derived for forms I and II. They are easily obtained from equations (12), (13), and (14) by imposing the appropriate restrictions noted above.

Empirical Analysis

In the paper's empirical application, we estimate the three sets of production functions discussed in the preceding section. To summarize the specifications, they are as follows:

Form I: $Q = F(\mathbf{s}, \mathbf{z}, \beta) \cdot \exp[-A(\mathbf{x}, \mathbf{z}, \alpha)] \cdot \exp(\varepsilon)$

Form II: $Q = F(\mathbf{s}, \mathbf{z}, \beta) \cdot \exp[-A(\mathbf{x}, \mathbf{z}, \alpha) \cdot e]$

Form III: $Q = F(\mathbf{s}, \mathbf{z}, \beta) \cdot \exp[-A(\mathbf{x}, \mathbf{z}, \alpha) \cdot e] \cdot \exp(\varepsilon)$

where $\varepsilon \sim N(0, 1)$ and $e \sim N(\mu, 1)$. In the noninteractive specification for each form, all elements of the vector $\mathbf{z}$ are zero.

Data

The data consist of 107 annual observations of quantities and prices for output and five inputs (land, machinery, fertilizer, pesticides, and miscellaneous inputs) for wheat farms in Kansas during the period 1973–90. The farms were selected from the computerized farm accounting records of the Farm Management Data Bank, Department of Agricultural Economics, Kansas State University (Langemeier).

To permit the analysis to focus on damage control for a single output and to avoid aggregation issues, farm observations selected for this study devoted at least 95% of row crop acreage to wheat and received at least 90% of farm income from the sale of wheat. Firm-level data from the Data Bank were supplemented with state-level price data (USDA, annual series) for prices unavailable at the farm level. All input and output variables were divided by their respective means to facilitate convergence in nonlinear estimation. A copy of the data used and additional details about data construction are available upon request from the authors.[3]

Separability Pretests

Since a form of separability is imposed in both the interactive and the noninteractive specifications, pretests for separability were conducted before estimating forms I–III. The inputs can be partitioned such that $\mathbf{s}$ appears only in $F(\cdot)$ and $\mathbf{x}$ appears only in $A(\cdot)$ if the marginal rate of substitution (MRS) between all pairs of inputs in $\mathbf{s}$ is independent of $\mathbf{x}$, and vice-versa. Neither $\mathbf{x}$ nor $\mathbf{s}$ need be separable from $\mathbf{z}$ since $\mathbf{z}$ appears in both aggregator functions $F(\cdot)$ and $A(\cdot)$ in the three forms. In the absence of clear evidence that an input is separable from some other inputs, it should be included in the potentially interactive subset $\mathbf{z}$. Thus, the purpose of the separability pretests is to determine which inputs can be clearly assigned to the noninteractive abatement subset $\mathbf{x}$, which can be clearly assigned to the noninteractive direct production input subset $\mathbf{s}$, and which cannot be so assigned.

Because of the frequent sensitivity of test conclusions to choice of functional form (Baffes and Vasavada; Berndt, Darrough, and Diewert), two flexible functional forms were employed in conducting the separability tests: translog and quadratic. On a priori grounds, we initially assigned pesticides to the damage control subset $\mathbf{x}$ (so $\mathbf{x}$ only contained one element) and all other inputs (land, fertilizer, machinery, and miscellaneous inputs) to the direct production input subset $\mathbf{s}$. To move an input from $\mathbf{s}$ to the common subset $\mathbf{z}$, we required only that separability from $\mathbf{x}$ (the null hypothesis) be rejected at the 0.10 level for any subset containing the input in question, with at least one functional form. This is a very weak rejection criterion and is based on the seriousness of the type II error relative to a type I error. Inappropriately removing an input from the interactive

---

[3] Appreciation is extended to Larry Langemeier and the Kansas State University faculty for access to the extensive data in the farm management data bank. Any release of data used in this study is subject to the conditions for research data access maintained by the Kansas Farm Management Associations. These conditions include anonymity of individual observations. Observations are identified in our data set only by observation number and not by farm or regional code.

subset could have a far greater adverse impact on model inferences than inappropriately including an input in that subset; estimation of the final production function with interactive abatement specifications can determine the actual extent of the interaction.

We failed to reject weak separability of any pair of production inputs from pesticides with either functional form. We also failed to reject weak separability of land, machinery, and miscellaneous inputs from pesticides with either functional form. However, weak separability of the subset that included all production inputs was rejected with the translog function. Since we failed to reject weak separability of land, machinery, and miscellaneous inputs from pesticides with either functional form, these inputs are legitimately retained in **s** and pesticides in **x**. Each of these inputs therefore can be excluded from **z**. This leaves only fertilizer in **z**.

To further examine this test conclusion, weak separability of land, machinery, and miscellaneous inputs from pesticides was maintained in a respecification of the quadratic and translog functional forms. Weak separability of fertilizer from pesticides and pesticides from fertilizer was again tested and rejected. Thus, the need for an interactive version of the damage abatement function is supported by the separability test results. The extent of fertilizer's interaction with other inputs, both damage control and direct production inputs, must be determined by estimation of the production function. All that can be determined from the separability pretest results is that the effects of fertilizer cannot be restricted to the subset of direct production inputs in specifying the damage function.[4]

Estimation Details

In forms I–III, the $F(\cdot)$ function was assumed to be Cobb-Douglas, i.e.,

$$(17)\quad F(\cdot) = \prod_{k=1}^{3} s_k^{\beta_k} z^{\gamma}$$

where s = {land, machinery, miscellaneous inputs} and z = fertilizer. As noted earlier, the Cobb-Douglas specification for $F(\cdot)$ is restrictive; it has been assumed here for empirical tractability. For the function $A(\cdot)$ within $g(\cdot)$ the following quadratic specification was assumed:

$$(18)\quad A(\cdot) = \alpha_0 + \alpha_1 x + \alpha_2 z + \alpha_3 x^2 + \alpha_4 z^2 + \alpha_5 xz$$

where x denotes pesticides. The input composition of the two functions $F(\cdot)$ and $A(\cdot)$ was based on separability test results reported above. Results from the estimation of the production function in form III with a quadratic form for $A(\cdot)$ as in equation (18) showed that the null H_0: $\alpha_3 = \alpha_4 = \alpha_5 = 0$ cannot be rejected (P value = 0.4057). Consequently, the simpler linear specification $A(\cdot) = \alpha_0 + \alpha_1 x + \alpha_2 z$ was adopted.

Both interactive and noninteractive specifications for the three forms I, II, and III were estimated using the method of maximum likelihood. The loglikelihood function for form III was set out in equation (10). The corresponding LLF for forms I and II can be derived from equation (10) under the appropriate restrictions on μ and $B(\cdot)$ noted earlier.

To justify the distributional assumption underlying the maximum likelihood estimation procedure, we tested for normality using the errors of the least-squares estimation of ln Q on ln $F(\cdot)$ where $F(\cdot)$ is defined in equation (17). Observe that in all three forms the common underlying equation is $\ln Q = \ln F(\cdot) + \vartheta$ as noted in equation (8). The models differ in the specification of the error ϑ. Thus, the test for normality (see Kiefer and Salmon for details) was performed using the normalized residuals $\hat{\vartheta}^* = (\hat{\vartheta} - \bar{\hat{\vartheta}})\sigma_{\hat{\vartheta}}^{2}$. The null hypothesis that $\hat{\vartheta}^*$ is distributed as a normal variate was not rejected. The chi-squared test statistic was 0.5799 (df = 2, P value = 0.3742).

To provide a benchmark for comparison, we also estimated a standard Cobb-Douglas production function (which treats all inputs as direct production inputs) using a subset of our data; in this subset all observations with zero level of pesticide usage were deleted. The loglinear form was estimated as follows: $\ln Q = \sum_{k=1}^{4} \beta_k \ln S_k + \gamma \ln z + u$ where $S \equiv$ {land, machinery, miscellaneous inputs, pesticides} and $u \sim N(0, \sigma_u^2)$.

Production Function Estimation Results

Parameter estimates for each of the seven alternative specifications are reported in table 1. Although three of the five parameter estimates for the standard Cobb-Douglas production function are significant at the 0.05 level, both the interactive and noninteractive forms I, II, and III statistically dominate the Cobb-Douglas specification. The loglikelihood function value cannot be used directly to compare these models since the number of observations is different

[4] The separability test details are available upon request from the authors.

Table 1. Parameter Estimates under Alternative Specifications

		Models						
			Form I		Form II		Form III	
Parameter	Explanation	Cobb-Douglas (CD)	Noninter-active	Inter-active	Noninter-active	Inter-active	Noninter-active	Inter-active
β_1	Land	0.7166	0.6868	0.6961	0.6761	0.6757	0.6708	0.7188
		(12.392)	(17.322)	(17.302)	(16.897)	(16.708)	(16.926)	(17.813)
β_2	Machinery	0.1767	0.0805	0.0796	0.0909	0.0919	0.0972	0.0817
		(2.550)	(2.095)	(2.051)	(2.357)	(2.353)	(2.587)	(1.992)
β_3	Misc.	0.0587	0.1782	0.1852	0.1724	0.1719	0.1699	0.1638
		(0.798)	(3.892)	(4.322)	(4.089)	(3.901)	(3.988)	(4.460)
γ	Fertilizer	0.0931	0.0721	0.0947	0.0697	0.0689	0.0703	0.1253
		(2.299)	(2.655)	(2.968)	(2.547)	(2.215)	(2.637)	(3.751)
α_0	Intercept	—	1.0258	0.9641	0.2455	0.2450	1.1550	0.6951
			(46.108)	(18.327)	(20.527)	(16.591)	(24.666)	(36.129)
α_1	Pesticides	—	−0.0292	−0.0317	−0.0079	−0.0079	−0.0356	−0.0096
			(2.546)	(2.655)	(3.105)	(2.985)	(3.817)	(1.960)
α_2	Fertilizer	—	—	0.0542	—	−0.0005	—	0.0638
				(1.290)		(2.985)		(3.307)
μ	Mean	—	—	—	4.201	4.2031	0.8923	1.3044
					(19.836)	(19.870)	(23.561)	(19.659)
σ^2	Variance	—	0.0569	0.0564	—	—	—	—
			(10.311)	(9.958)				
ρ	Covariance	—	—	—	—	—	0.9823	1.0042
							(179.67)	(117.47)
β_4	Pesticides	0.0219	—	—	—	—	—	—
		(1.536)						
LLF	Loglikelihood	96.17	199.73	200.59	200.87	200.88	201.46	208.33
AIC	Akaike's Crit.	89.17	192.73	192.58	193.87	192.88	193.46	199.33
SC	Schwarz's Crit.	80.70	183.78	181.89	184.52	182.19	182.77	187.30
N	No. of observ.	83	107	107	107	107	107	107

Note Absolute values of asymptotic *t*-ratios are in parentheses.

for the Cobb-Douglas. However, on the basis of the Schwarz criterion, which can be used to examine alternative specifications with unequal numbers of observations, each of the alternative models is preferred over the Cobb-Douglas.

In forms II and III, the parameter α_2 is significantly different from zero, rejecting the null hypothesis that fertilizer and pesticides have no interaction within the damage abatement component of the production function. However, the noninteractive specification is not rejected in form I.

Since forms I–III are parametrically nonnested models, Akaike's criterion can be used for model selection.[5] Under this criterion, the interactive form III model clearly dominates both the interactive and noninteractive specifications of forms I and II. The same conclusion is reached using the Schwarz criterion.

Recall from the discussion in the previous section that a necessary condition for rejecting form III in favor of either forms I or II is the restriction $\rho = 0$ where ρ is the covariance between the two random variables e and ε in form III. It is evident from table 1 that $\hat{\rho}$ is highly significant, clearly rejecting both forms I and II. In light of our interpretation of the random variables e and ε in form III, a positive and significant $\hat{\rho}$ seems eminently plausible.

In each of the three forms, since $g(\cdot)$ denotes the abatement function, the qualitative effect of pesticides and fertilizer on damage abatement is captured by $[\partial g(\cdot)/\partial x] \doteq -\alpha_1$ and $[\partial g(\cdot)/\partial z] \doteq -\alpha_2$ respectively, and the nature of the interaction between pesticides and fertilizer in the abatement process is conveyed by $[\partial^2 g(\cdot)/\partial x \partial z] \doteq \alpha_1\alpha_2$, where $\doteq$ denotes "same sign as." In discussing these effects, we focus on form III

[5] An alternative model selection criterion, likelihood dominance, has recently been proposed by Pollak and Wales. The ranking of the models using this criterion was found to be identical to that using Akaike's criterion

Table 2. Marginal Product and Variance Effect of Pesticides and Fertilizers

	Form I		Form II		Form III	
At Sample Means:	Noninteractive	Interactive	Noninteractive	Interactive	Noninteractive	Interactive
MP of pesticides	0.0292	0.0317	0.0315	0.0313	0.0269	0.0150
	(2.546)	(2.655)	(3.066)	(3.011)	(3.789)	(2.144)
Variance effect of pesticides	0.0017	0.0018	−0.0002	−0.0002	−0.0037	0.0035
	(2.465)	(2.561)	(2.665)	(2.299)	(1.808)	(2.335)
MP of fertilizers	0.0721	0.0405	0.0698	0.0707	0.0703	0.0257
	(2.655)	(1.103)	(2.547)	(2.144)	(2.637)	(0.782)
Variance effect of fertilizer	0.0042	0.0055	0.0271	0.0268	0.0273	0.0258
	(2.566)	(2.823)	(2.546)	(2.199)	(2.636)	(2.155)

Note Absolute values of asymptotic *t*-ratios are in parentheses

since it clearly dominates the other two forms.

The results show that while pesticides abate damage, fertilizer increases it. Despite the damage-increasing role, however, the marginal product (MP) of fertilizer is positive in all three forms (these results are presented later). Fertilizer's damage-increasing effect stems from the fact that, while fertilizer increases wheat yield, it also enhances weed growth The principal pesticides used on Kansas wheat are herbicides. Thus, one can expect fertilizer to reduce the effectiveness of a given dose of herbicides by encouraging weed growth. This conjecture is supported by the form III result, $[\partial^2 g(\cdot)/\partial z \partial x] \doteq \hat{\alpha}_1 \hat{\alpha}_2 < 0$; that is, fertilizer has a negative effect on pesticide's role in abating damage. Importantly, form II results suggest the opposite conclusion, underscoring the importance of correct functional form specification. All forms, both interactive and noninteractive, reveal pesticides to be significantly damage abating, but only the form III interactive model results indicate the significant damage-enhancing effect of fertilizer and its negative effect on pesticides' role in damage abatement.

Mean and Variance Effects of Pesticides and Fertilizer

The expressions for the mean and variance effects of pesticides and fertilizer were derived for form III in equations (12) and (13). The corresponding expressions for the other two forms follow under appropriate restrictions. The mean effect of an input is simply its marginal product evaluated at the mean. The relevant findings are presented in table 2.

Perhaps the most striking result is that the MP of both pesticides and fertilizer under interactive form III is only about half the magnitudes estimated under the five alternative forms.[6] Although counter to Carrasco-Tauber and Moffitt's observation for aggregate state-level data, our finding that incorrect model specification leads to substantial overestimation of pesticide MP strongly supports the assertion of Lichtenberg and Zilberman. Clearly, this result has important policy implications, which are deferred to the next section.

In all six specifications, fertilizer has a variance-enhancing effect on output. Interestingly, under form III, when the interaction between pesticides and fertilizer in damage abatement is considered, pesticides are also found to be variance increasing. The opposite is true in form II. The functional form for form I precludes variance-reducing inputs.

The "risk increasing" (Just and Pope) role of both chemical inputs under interactive form III may warrant explanation. Fertilizer-induced higher yield variability is likely attributable to the larger difference in crop yield between favorable and unfavorable conditions with larger amounts of fertilizer (Duvick). This difference is likely to be particularly acute in our data set because almost all the farms are nonirrigated. The variability of moisture, stemming from the fluctuation in rainfall, is also likely to enhance variability in the incidence of foliar pathogens (rusts, mildews, blasts, smuts). This effect is

---

[6] We also estimated the MP of pesticides under the Cobb-Douglas (CD), translog (TL), and quadratic (QD) forms The CD and TL were estimated using the truncated sample of 83 observations, while the QD was estimated using the full data set The two widely used specifications, TL and QD, appear to considerably overstate the MP of pesticides, which is 0.0612 and 0.0324, respectively under the two forms The MP estimate under CD is lower, 0.0219, but it is almost 1.5 times higher than the estimate under interactive form III

compounded by the effect of fertilizer on weed growth as noted earlier. Thus, although the risk-increasing role of pesticides and fertilizer may at first appear counterintituive, it seems plausible when the interaction between fertilizer and pesticides is considered. Importantly, this finding is not unique to our study. Roumassett et al. (pp. 228–29) cite other studies that report similar results for fertilizer. Recent studies by Pannell (1991, 1995) and by Horowitz and Lichtenberg (1993, 1994) arrive at the same conclusion for pesticides. Pannell (1995) further notes that herbicides are the primary cause of the risk-increasing effects of pesticides in his data. Insecticides did not show the same effect, but they are not used as heavily as herbicides on Kansas wheat.

Although modern farming practices that use significant amounts of agricultural chemicals have enhanced yield variability, they have also increased mean yield levels considerably (Duvic). As long as the mean increase is sufficiently large, chemical usage will continue to be a rational choice for farmers despite their risk-averse preferences and the increased yield variability.

Policy Implications

In this section we examine the inferential consequences of alternative production function specifications. Using the interactive versions of forms I, II, and III, we compare (*a*) the optimal demand for pesticides, fertilizer, and other inputs at mean prices under a mean-variance utility framework; (*b*) the threshold pesticide price that would cause pesticide demand to drop to zero; and (*c*) the price at which pesticide demand under each form will be reduced by half.

A risk-averse producer's input choice problem in the linear mean-variance framework is set out as follows:

$$(19)\quad \max_{s,z,x}\ H = \bar{Q} - \frac{\phi}{2}\bar{Q}^2\{\exp[B(\cdot)] - 1\} - \sum_k w_k s_k - w_z z - w_x x$$

where $\bar{Q}$ is the expected output level; $\bar{Q}^2\{\exp[B(\cdot)] - 1\}$ is output variance defined in equations (11a) and (11b); ϕ denotes the Arrow-Pratt measure of risk aversion; s, z, and x are the input levels defined in equation (17), w_k, w_z, and w_x denote the price of s_k, z, and x, normalized by output price. The specific form of the objective function under forms I, II, and III is obtained by making appropriate substitutions for $\bar{Q}$ and $B(\cdot)$ in equation (19).

Let $y \equiv \{s, z, x\}$ denote the choice vector of the optimization problem in equation (19). Using the parameter estimates from each of the three interactive forms, and setting $\phi = 0.3$, the function in equation (19) was numerically maximized (using the software Mathematica) to yield the optimal choice vector $y^* \equiv \{s^*, z^*, x^*\}$. In the interest of brevity, only the optimal levels of pesticides and fertilizer under interactive forms I–III are reported in table 3. Optimal demands for both x and z are considerably smaller under form III than under forms I or II. In fact, pesticide demand under form I is over three times larger than that under form III, and fertilizer demand is ten times larger. Thus, academic and extension recommendations based on forms I and II will vastly overstate the optimal pesticide and fertilizer use if form III is, in fact, correct. Also, recall from table 2 that there was only a slight difference in MP of pesticides under interactive forms I and II (1.3%); yet the difference in pesticide demand under the two specifications is over 50%. This result, explained by the high degree of nonlinearity of the objective function in equation (19), shows that mere MP comparison may mask the larger inferential consequences of the various specifications.

To underscore the sensitivity of results to the less general stochastic specifications, we also computed the threshold price for pesticides. This threshold is defined as the price at which the optimal demand for pesticides drops to zero. To numerically compute this threshold, we gradually increased the pesticide price, w_x, solving for y^* at each level of w_x, until x^*, the pesticide demand, was equal to zero. The threshold price level is reported in the third row of table 3. A tax levied on pesticides may be a possible policy tool to drastically reduce its usage. Our results show that the answer to what this tax should be is extremely sensitive to proper specification of the stochastic elements in the production process. Under form III, the price increase needs to be 71.2% over the base level of 0.0111, which is the mean normalized pesticide price. In contrast, under forms I and II the pesticide price must be 43 and 26 times the base level for demand to drop to zero. Thus, policies intended to reduce pesticide use, while reserving them for critical cases, by raising pesticide prices do not have nearly the price latitude implied by stochastic specifications that do not take randomness in both the abatement function (form I) and the direct production process (form II) into account.

Table 3. Optimal Input Usage and Compensation under Alternative Forms

	Interactive Form		
	I	II	III
Optimal level of			
Pesticides	141.202	70.354	45.55
Fertilizer	10.301	6.207	1.028
Threshold price for pesticides[a]	0.492	0.295	0.019
Price at which pesticide demand will be halved[b]	0.0784	0.0574	0.0125

[a] Threshold price is the normalized price at which optimal demand for pesticides drops to zero. Mean normalized price is 0.0111.
[b] The price at which the demand for pesticides under each form will be half the optimal level stated in the first row of this table.

Complete elimination of pesticide use through price increases may not be economically viable nor socially desirable except in the most extreme cases. With this in mind, we computed the price at which pesticide usage will drop to half of the optimal for each of the three specifications. This price is reported in the last row of table 3. Importantly, in all three forms, the price increase required to reduce x^* to $x^*/2$ is much smaller than half the price increase required to reduce x^* to zero. For example, in form III, only a 12.6% increase in price over the base of 0.0111 reduces demand by half; in contrast, it may be recalled that to reduce demand to zero a 71.2% price increase was required (see the threshold price). This difference in price increases is explained by the nonlinearity of the pesticides demand schedule.

As in the case of threshold price, forms I and II grossly underestimate the demand response to pesticide increases. Under forms I and II, the required price has to be 7.1 times and 5.2 times the base level to reduce demand by half. These figures can be contrasted to that for form III, where a price only 1.13 times the base level achieves the desired demand reduction.

Summary and Conclusions

Farmers are increasingly subject to environmentally based regulation of chemical damage control inputs to production. Efforts to assess the effects of regulatory policy on these inputs are made difficult by the fact that, unlike direct inputs, they represent a response to unique field conditions, and thus are likely to assume zero values in many circumstances. Treating them as just another direct input is therefore unsatisfactory since widely used functional forms that permit nonzero output with a zero input are unrealistic for various reasons (e.g., input levels have no effect on output variance). This problem is overcome by replacing the damage control inputs in the production function with an abatement function that returns a strictly positive value for all nonzero values for its argument. This leads to the issues examined in this study: the interaction of inputs within the abatement function (e.g., fertilizer and pesticide) and the stochastic structure of the abatement and general production functions.

With regard to the first issue, separability pretests were conducted to identify inputs that clearly do not interact within the abatement function, leading to an exhaustive division of inputs into direct production only, abatement only, and a subset common to both the production and abatement functions. This separation of inputs is essential for empirically valid production function specification.

With regard to the second issue, three model forms were studied. The first relied on an exact (nonstochastic) abatement function, with a multiplicative random element as in traditional forms such as Cobb-Douglas. This form (I) was found to be deficient on two counts: (*a*) it assumes damage control inputs at levels that preclude any uncertainty in abatement, a model that may be appropriate only if damage control inputs are used at such a high level so as to preclude any randomness in the abatement process; and (*b*) it implies that the signs of the mean and variance effects are the same; i.e., output-mean-increasing inputs are necessarily output-variance increasing.

Allowing uncertainty only in the abatement function led to the second form. This form (II) is analytically tractable in a variety of cases and permits mean and variance effects that differ in sign, but it requires an exact relation between direct inputs plus the abatement function and observed output. It is unrealistic to assume that, in practice, explicit combinations of inputs and realized abatement will lead to exactly the same output; in reality we must average over a wide assortment of factors that influence final output.

The third form (III) allows uncertainty in both the abatement and the overall production process. Uncertainty in the abatement function is especially important at the lower application levels of damage control inputs common in modern agriculture. At the same time, the traditional stochastic determinants of output given inputs still apply (e.g., variability in rainfall, temperature, and soil fertility all lead to random errors in the production relation). In this form, inputs can be output variance increasing or decreasing despite being mean increasing. The generality in form III comes at the expense of analytic complexity. However, a particular combination of widely used functions, the Cobb-Douglas for the direct production part and the exponential form for the abatement function, when combined with Gaussian errors, leads to an analytically tractable stochastic specification.

These specification issues were examined empirically using a sample of four years of data on Kansas wheat farms. It was found that pesticides and fertilizer do need to be modeled differently from direct production inputs, that fertilizer had both direct production and damage abatement effects, and that both the abatement function and the production function must be treated as stochastic. Our findings showed that model misspecification of the stochastic nature of the production process led to serious overestimation of marginal physical productivity of both the damage control input (pesticides) and the interactive input (fertilizer). The analysis also showed that not accounting for both types of stochastic errors resulted in gross underestimation of the demand responsiveness of an increase in pesticide prices. Such an underestimation could result in severe hardship to the agricultural community and a welfare reduction to society in general when a policy intended to restrict pesticide usage to critical applications results de facto in an outright ban.

[Received March 1996; final revision received March 1997.]

References

Akaike, H. "Information Theory and an Extension of the Maximum Likelihood Principle." *Second International Symposium on Information Theory.* N.B. Petrou and F. Caski, eds., pp. 267–81, 1973.

Avery, D. "Saving the Planet with Pesticides: Increasing Food Supplies While Preserving the Earth's Biodiversity." *The True State of the Planet,* chap. 2. R. Bailey, ed. New York: The Free Press, 1995.

Baffes, J., and U. Vasavada. "On the Choice of Functional forms in Agricultural Production Analysis." *Appl. Econ.* 21(August 1989):1053–61.

Berndt, E.R., M.N. Darrough, and W.E. Diewert. "Flexible Functional Forms and Expenditure Distribution: An Application to Canadian Consumer Demand Functions." *Int. Econ. Rev.* 18(October 1977):651–75.

Blackorby, C., D. Primont, and R.R. Russell. "On Testing Separability Restrictions with Flexible Functional Forms." *J. Econometrics* 5(March 1977):195–209.

Carrasco-Tauber, C., and L.J. Moffitt. "Damage Control Econometrics: Functional Specification and Pesticide Productivity." *Amer. J. Agr. Econ.* 74(February 1992):158-62.

Chambers, R.G., and E. Lichtenberg. "Simple Econometrics of Pesticide Productivity." *Amer. J. Agr. Econ.* 76(August 1994):407–17.

Dionne, G., and L. Eeckhoudt. "Self Insurance, Self Protection and Increased Risk Aversion." *Econ. Letters* 17(1985):39–42.

Duvick, D.N. "Possible Genetic Causes of Increased Variability in U.S. Maize Yields." *Variability in Grain Yields.* J.R. Anderson and P.B.R. Hazell eds., pp. 147–56. Baltimore MD: John Hopkins University Press, 1989.

Ehrlich, L., and G.S. Becker. "Market Insurance, Self Insurance and Self Protection." *J. Polit. Econ.* 80(July/August 1972):623–48.

Feder, G. "Pesticides, Information and Pest Management Under Uncertainty." *Amer. J. Agr. Econ.* 61(February 1979):97–103.

Hiebert, L.D. "Optimal Loss Reduction and Increases in Risk Aversion." *J. Risk and Insurance* 56(June 1989):300–05.

Horowitz. J.K., and E. Lichtenberg. "Insurance, Moral Hazard and Chemical Use in Agriculture." *Amer. J. Agr. Econ.* 75(November 1993):926–35.

___. "Risk-Reducing and Risk-Increasing Effects of Pesticides." *J. Agr. Econ.* 45(January 1994):82–88.

Just, R.E., and R.D. Pope. "Stochastic Specification of Production Functions and Economic Implications." *J. Econometrics* 7(February 1978):67–86.

Kiefer, N., and M. Salmon. "Testing Normality in Econometric Models." *Econ. Letters* 11(1983):123–28.

Langemeier, L.N. "Farm Management Data Bank Documentation." Department of Agricultural Economics Staff Paper No. 90-10, Kansas State University, April 1990.

Lichtenberg, E., and D. Zilberman. "The Econometrics of Damage Control: Why Specification Matters." *Amer. J. Agr Econ.* 68(May 1986):261–73.

Mood, A.M., F.A. Graybill, and D.C. Boes. *Introduction to the Theory of Statistics*, 3rd ed. New York: McGraw Hill, 1974.

National Research Council. *Regulating Pesticides in Food. The Delaney Paradox.* Washington DC: National Academy Press, 1987.

Pannell, D.J. "Optimal Herbicide Strategies for Weed Control Under Risk Aversion." *Rev. Agr. Econ.* 17(September 1995):337–50.

___. "Pests and Pesticides, Risk and Risk Aversion." *Agr Econ.* 5(August 1991):361–83

Pollak, R.A., and T.J. Wales. "The Likelihood Dominance Criterion: A New Approach to Model Selection." *J. Econometrics* 47(February/March 1991):227–42.

Pope, R D , and R.A. Kramer. "Production Uncertainty and Factor Demands for the Competitive Firm." *S. Econ. J.* 46(October 1979):489–501.

Regev, U , H. Shalit, and A.P. Gutierrez "On the Optimal Allocation of Pesticides with Increasing Resistance." *J. Environ. Econ and Manage.* 10(March 1983):86–100.

Roumassett, J.A., M.W. Rosegrant, U.N. Chakravorty, and J.R. Anderson. "Fertilizer and Crop Yield Variability: A Review." *Variability in Grain Yields.* J.R. Anderson and P.B.R Hazell, eds., pp. 223–33. Baltimore MD: John Hopkins University Press, 1989.

Schwarz, G. "Estimating the Dimension of a Model." *Annals of Statist.* 6(March 1978):461–64.

Taylor, C.R., J.B. Penson, E.G. Smith, and R.D. Knutson. "Economic Impacts of Chemical Use Reduction on the South." *S. J Agr. Econ.* 23(July 1991):15–23.

U.S Department of Agriculture. *Agricultural Prices.* Washington DC, annual series.

___ *Agricultural Statistics.* Washington DC, annual series.

___. *Field Crops Production, Disposition and Value.* Washington DC, annual series.

___. *Meat Animals Production, Disposition and Value.* Washington DC, annual series.

U.S. Department of Agriculture, Economic Research Service. *Situation and Outlook Reports: Resources.* Washington DC, annual series.

U.S. Department of Agriculture, National Agricultural Statistics Service. *Annual Price Summaries.* Washington DC, annual series.

U.S. Environmental Protection Agency (USEPA). *Summary Results of EPA's National Survey of Pesticides in Drinking Water Wells.* Washington DC, 1990.

Weersink, A., W. Deen, and S. Weaver. "Defining and Measuring Economic Threshold Levels." *Can. J. Agr. Econ.* 39(December 1991):619–25